Constructing A Scoring Support Approach Model For Classical Ballet: Combining Motion Capture And Statistical Science

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ABSTRACT

This study employs motion capture and statistics to develop an objective, rational scoring system for classical ballet and uses the results to construct a scoring support approach model. Specifically, the study focuses on classical ballet, using interviews with judges and other methods to clarify the correlation between practical skills and barre training as well as between technical and artistic scores. This process revealed that practical skills are a combination of movements practiced at a barre and that technical evaluations of barre training have a direct link to overall evaluations of practical skills. Based on these insights, the authors broke barre training down into individual movement elements and movement factors, then clarified the causal relationships among them using positioning data gathered from motion capture equipment and from scoring results by professional judges. The knowledge gained was, in turn, used to actually support the scoring of classical ballet barre training, and the desired results were obtained.

Keywords: Classical Ballet; Motion Capture; Scoring Support Approach Model

INTRODUCTION

The classical ballet scoring that is done by judges is not guided by a clear set of scoring criteria. Instead, each judge relies on his or her personal experience (standards of judgment) to produce a subjective score. The interval between the static and dynamic elements that make up each movement in classical ballet are complicated and instantaneous—and because it is tacitly understood that judges score according to the element of movement that they are focusing on, there can be significant variations in scoring results. It is for this reason that judges could use an objective and rational scoring support tool to help them score ballet performances. In response to this need, the authors employed motion capture and statistics to construct a rational classical ballet scoring support approach model.

Specifically, the authors looked at performance elements like the grand plié and cambré, then broke down the individual elements of movement that make up each of the varied positions based on the basic positions that comprise barre training. Next, the authors used motion capture to calculate positioning information for each movement factor included in body angle, smoothness, and other components of the main positions. Each movement element was then examined to determine its level of impact on overall score. The insights obtained from this process were used to create a statistical model of the causal relationships that determine by what standard scores on individual elements affect the total score - in other words, to define the standards affecting the relative weight of each score.

BACKGROUND

How Classical Ballet is Currently Judged

Classical ballet judging today is ambiguous, guided by no consistent set of evaluation criteria. As a result, it is common to have scores that vary widely among judges - a problematic situation that could be improved (Ota.H).

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Every classical ballet competition uses a different scoring system, but the typical standard involves two five-point scales - one for technical performance and one for artistic performance. In this case, scoring tends to focus on the following five areas.

1. Ability to understand and express the variation: Understanding the role of the and expressing it well
2. Appearance: Articulation and openness of the hip joints
3. Musicality: Correct musical expression, rhythm, keeping time with the music
4. Technique: correct performance of each movement, positioning, rotation, jumping, balance, etc.
5. Potential: Likelihood that the dancer will be able to make a name for themselves with continued growth and practice

However, this does not mean that scores are determined from these five areas; it only means that they are points of focus that guide judges to assign technical and artistic scores based on their own subjective impressions. Even though many competitions take steps to reduce scoring variation with strategies like throwing out high and low scores, this alone does not reduce the actual score variation among judges. The real problem causing the variation is the ambiguity in scoring criteria.

When six professional judges were surveyed on the current state of ballet judging, their feedback indicated that the lack of a detailed scoring standard for classical ballet made it extremely difficult for scoring to be done fairly. One judge scored a competitor higher than the one who took first place in an actual competition, while another scored that same competitor near the bottom of the group.

The judges themselves are aware that there is a problem in the current situation, where variation in scores arises because of a lack of evaluation criteria—meaning that every person has different standards of judgment. The lack of consistency in evaluation criteria also causes problems in coaching and a performer might work to improve a low score received at one competition only to be scored poorly in their strong area at another. In this way, ambiguous evaluation criteria hinder ballet dancers from improving their skills.

Prior Research

Prior research on similar topics was done by Yurie Ino et al (2011) who analyzed street dance moves and applied the results to dance instruction. The difference between expert and novice movements was clarified and made explicit by analyzing data obtained from motion capture equipment with the aim of sharing the insights gained with novice dancers to improve the efficiency of their training. Because the “expert” and “novice” designations were based on the number of years of dancing experience, the difference between good and bad movements remained implicit, and the study did not make clear the relationship of good and bad movements to actual evaluations.

To investigate causal relationship that is in implicit phenomenon, Amasaka (Aoyama Gakuin University) applied “product development technological method - Customer Science” (Amasaka, 2002a, 2008a). In this study, the authors used this approach to clarify causal relationship between dancers’ movements and evaluations of judges.

CONSTRUCTING A SCORING SUPPORT APPROACH MODEL FOR CLASSICAL BALLET

By quantitatively capturing subjective human impressions of movement, this study aims to clarify and make explicit the relationship between classical ballet movements and the way those movements are evaluated. It also aims to address the problem of variation in scoring among classical ballet judges by constructing a scoring support model.

With these goals in mind, the authors established the classical ballet scoring support approach model in Figure 1 in the hopes of reducing scoring variations among judges.

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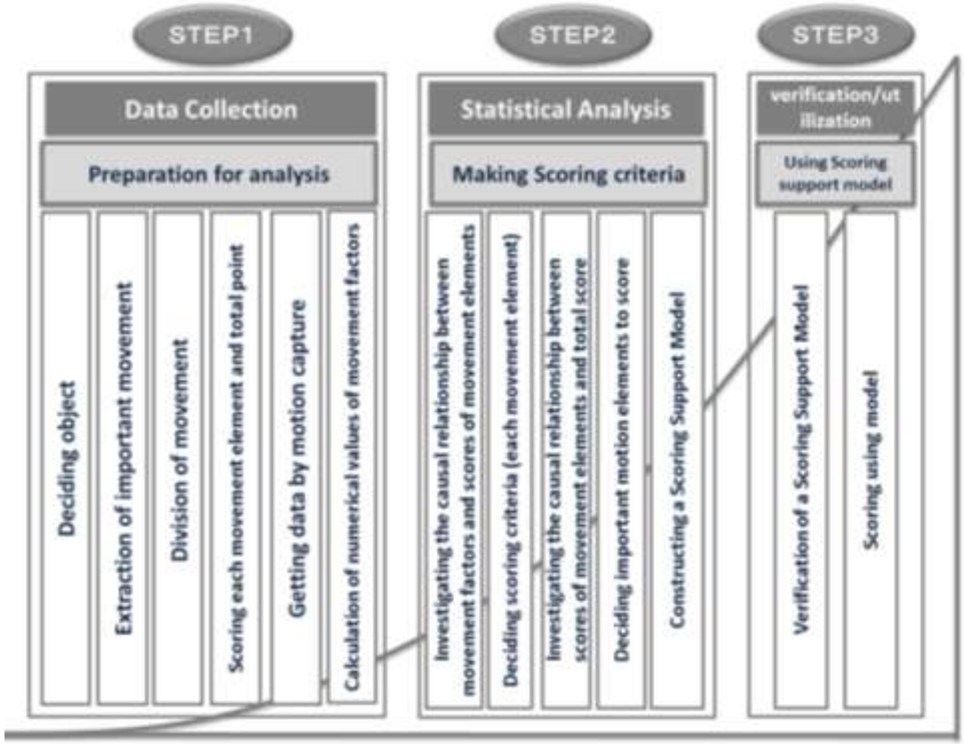

Figure 1: Scoring Support Approach Model for Classical Ballet

Deciding Movement for Analysis and Getting Data by Motion Capture

In this section, the authors define the movements that need to be analyzed in order to evaluate practical classical ballet skills and collect the required data.

To start, the following six insights were obtained through interviews with six professional judges:

1. It is difficult to directly consider artistic evaluations as long as the set standards for technical evaluations have not been achieved.
2. Practical skills are applied movements and a combination of basic movements.
3. The integrity of applied movements is proportional to the integrity of individual basic movements.
4. Basic movements are acquired through barre training.
5. The plié is a basic movement performed during barre training.
6. The rond de jambe is a movement performed during barre training that clearly demonstrates a dancer's proficiency.

Based on these insights, the authors decided to use the plié and rond de jambe movements as targets for their analysis. Next, an optical motion capture system was used to collect positioning data on the plié and rond de jambe movements of six dancers, two in each of three skill categories - expert (10-plus years of experience), intermediate (around five years of experience), and novice (only a few weeks of experience). Markers were placed on their bodies at 38 points and movement data were collected along xyz coordinates for each frame, which is equal to 1/480th of a second (see Table 1).

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Table 1: 1Frame Data by Motion Capture

17509 frames
q 480.00

Mark	Confiden	X axis	Y axis	Z axis
m 0x0000,	5.920726,	67.127083	317.340393	169.925827
m 0x0001,	3.000000,	115.088982	-13.095357	215.420486
m 0x0002,	-1.000000,	105.738022	91.111816	233.431976
m 0x0003,	3.000000,	135.298233	-94.418388	197.687866
m 0x0004,	4.498149,	157.909637	-180.063675	185.901596
m 0x0005,	3.000000,	146.032974	-239.291290	212.567154
m 0x0006,	7.802157,	165.768265	-233.366257	148.302063
m 0x0007,	-1.000000,	0.000000	0.000000	0.000000
m 0x0008,	-1.000000,	-188.537003	-247.377319	-169.508011
m 0x0009,	-1.000000,	-165.198059	-180.604065	-166.300629
m 0x000a,	5.892268,	-221.691299	-125.281754	-132.313080
m 0x000b,	3.000000,	-248.500931	-25.496517	-99.006142
m 0x000c,	10.596709,	-255.625443	82.392654	-82.651855
m 0x000d,	3.000000,	-194.816299	327.425568	-57.558224
m 0x000e,	3.928623,	-123.979950	502.358673	157.954498
m 0x000f,	3.000000,	-28.408493	599.220825	81.583572
m 0x0010,	4.799310,	-198.104919	499.861420	89.909348
m 0x0011,	-1.000000,	-82.608574	605.609802	-0.434121
m 0x0012,	-1.000000,	0.000000	0.000000	0.000000
m 0x0013,	3.000000,	-17.935163	252.193542	11.224072
m 0x0014,	3.301843,	11.130876	84.275749	0.170756
m 0x0015,	3.000000,	-164.374908	209.732727	173.060760
m 0x0016,	5.443317,	-214.426559	-31.011293	32.360119
m 0x0017,	3.000000,	-36.328434	-34.269772	222.469696
m 0x0018,	15.182865,	-66.583763	-916.320007	-2.045584
m 0x0019,	-1.000000,	0.000000	0.000000	0.000000
m 0x001a,	6.654889,	-166.503860	-899.043701	141.884537

Clarifying Scoring Criteria

The plié and rond de jambe movements used for analysis could be broken down into thirteen types of movement elements in five categories (see Table 2). The authors then clarified the causal relationships between (1) angle and smoothness in each part of the body (labeled "movement factors") during the thirteen individual types of movement elements and (2) scoring results. Interviews were conducted in order to determine the movement factors for each movement element and this information was used to examine which parts of the body should be focused on.

Table 2: Movement Element for Plié and Rond de Jambe

Plie			Cambre		Pointe			Battement			Preparation	
Demi 1	Demi 2	Grand	Cambre 1	Camble 2	en dehors	Tendeu	Arabesque	Battement 1	Battement 2	Rond de jambe	Preparation 1	Preparation 2

An eye-tracking camera was also used to conduct a line-of-sight analysis which revealed that the movement factors identified through the interviews were the same areas that viewers fixed their gaze on for relatively long periods of time. Using the positioning information obtained from the motion capture system, average cosine values for body angles were calculated and used to find numerical values for each movement factor.

The six professional judges were also shown videos of the thirteen types of movement elements performed by the six test subjects and asked to score them. This data were subjected to a multiple regression analysis to examine the degree of impact each of the movement factors had on movement element scores.

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When the multiple regression analysis was conducted on the grand plié, the movement factors were designated as explanatory variables, while movement element scores were designated as objective variables. The analysis yielded an R^{*2} coefficient of determination of 0.973, indicating explanatory power (see Table 3). Looking at the standardized partial regression, coefficient values allowed the authors to determine the level and direction of impact for each variable. It was discovered that performers who stick out their chests receive higher scores.

Table 3: Result of Multiple Regression Analysis for Grand Plié

	Standardized partial regression coefficient values
Constant	-
Chest	-0.349
Back	0.221
Heel	-1.495
Knee	-1.254

Using these results, it was possible to make “sticking out the chest” a key phrase to help score the grand plié. Other key scoring phrases for the grand plié included “lengthening the back”, “keeping the heel lifted”, and “pointing the knee and toes in the same direction”. Using the same approach, key scoring phrases were created for all thirteen elements of movement.

Next, the authors examined the relationship between the overall barre training score (which included the plié and rond de jambe) and the scores on each of the thirteen types of movement elements. Scores from the six professional judges evaluating each element of movement were used as explanatory variables, while overall barre training scores received from the same six judges were used as objective variables in a multiple regression analysis. Once the variables were selected using a stepwise regression method, partial regression coefficients revealed the level and direction of impact for each variable (see Table 4).

Table 4: Result of Multiple Regression Analysis

	Objective variables	Residual sum of squares	Multiple correlation coefficient	Contribution ratio R^2	R*^2
	Overall score	54.631	0.993	0.985	0.983
vNo	Explanatory variables	Residual sum of squares	Variation	Variance ratio	Partial regression coefficient
0	Constant Term	63.436	8.805	4.9964	2.689
1	Grand Plie	63.431	8.800	4.9934	0.226
2	Demi Plie 1	53.844	-0.788	0.4388	-
3	Demi Plie 2	53.943	-0.688	0.3828	-
4	Cambre 1	66.496	11.865	6.7326	0.262
5	Cambre 2	51.098	-3.534	2.0746	-
6	En Dehors	60.767	6.136	3.4818	0.219
7	Tendeu	54.084	-0.547	0.3036	-
8	Arabesque	51.055	-3.576	2.1012	+
9	Battement 1	68.907	14.275	8.1005	0.250
10	Battement 2	54.623	-0.008	0.0045	+
11	Rond de Jumbe	54.040	-0.591	0.3281	-
12	Preparation 1	53.141	-1.490	0.8414	+
13	Preparation 2	51.179	-3.452	2.0235	-

The analysis yielded an R^{*2} coefficient of determination of 0.985, indicating sufficient explanatory power. The explanatory variables were selected as follows: movement element D is the grand plié, movement element E is the cambre (1), movement element I is the en dehors, and movement element Q is the battement (1). The overall score for a barre lesson consisting of a grand plié and rond de jambe was found to be strongly impacted by these movement elements.

In addition, the partial regression coefficients for the grand plié (0.226), cambre (1) (0.262), en dehors (0.219), and battement (1) (0.250) were very similar. These analysis results indicate that an objective rational scoring is possible if these four movement elements are weighted equally when coming up with an overall barre training score. These results also make it possible to determine key scoring phrases that can be used to establish concrete scoring criteria (see Figure 2).

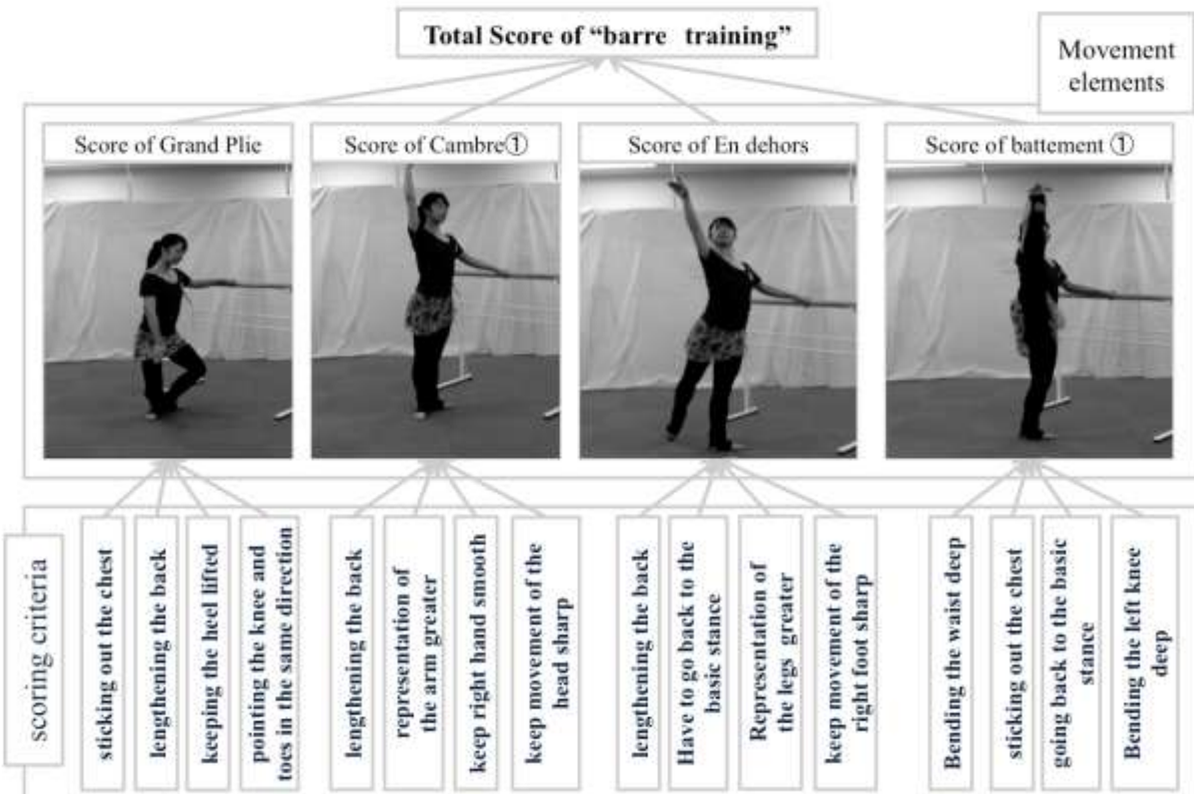

Figure 2: Scoring Criteria

VERIFICATION

The scoring support model created by the authors was verified to determine whether it was a practical way to offer clear scoring elements (movement elements) and scoring criteria (movement factors). There were two parts to the verification process. The first was creating a model that assigned the partial regression coefficients found in the multiple regression analysis as coefficients for each explanatory variable, and then calculating scores by substituting in new data. When these results were compared with scores from the six judges (generated using the convention scoring method), the rank correlation coefficient verified the effectiveness of the model. In the second part, interviews were conducted with the judges to examine the effectiveness and necessity of the scoring criteria created from the scoring support model. The judges verified that the model addressed a need in classical ballet judging.

Verification by Scoring Support Model

The relationship between overall scores and movement element scores, as well as between movement element scores and movement factor values, was clarified using the partial correlation coefficients calculated during

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the multiple regression analysis (see Figure 3). By making these consistent in a model formula, the authors were able to determine an overall score by substituting different values for the grand plié, cambre (1), en dehors, and rond de jambe (see Table 5).

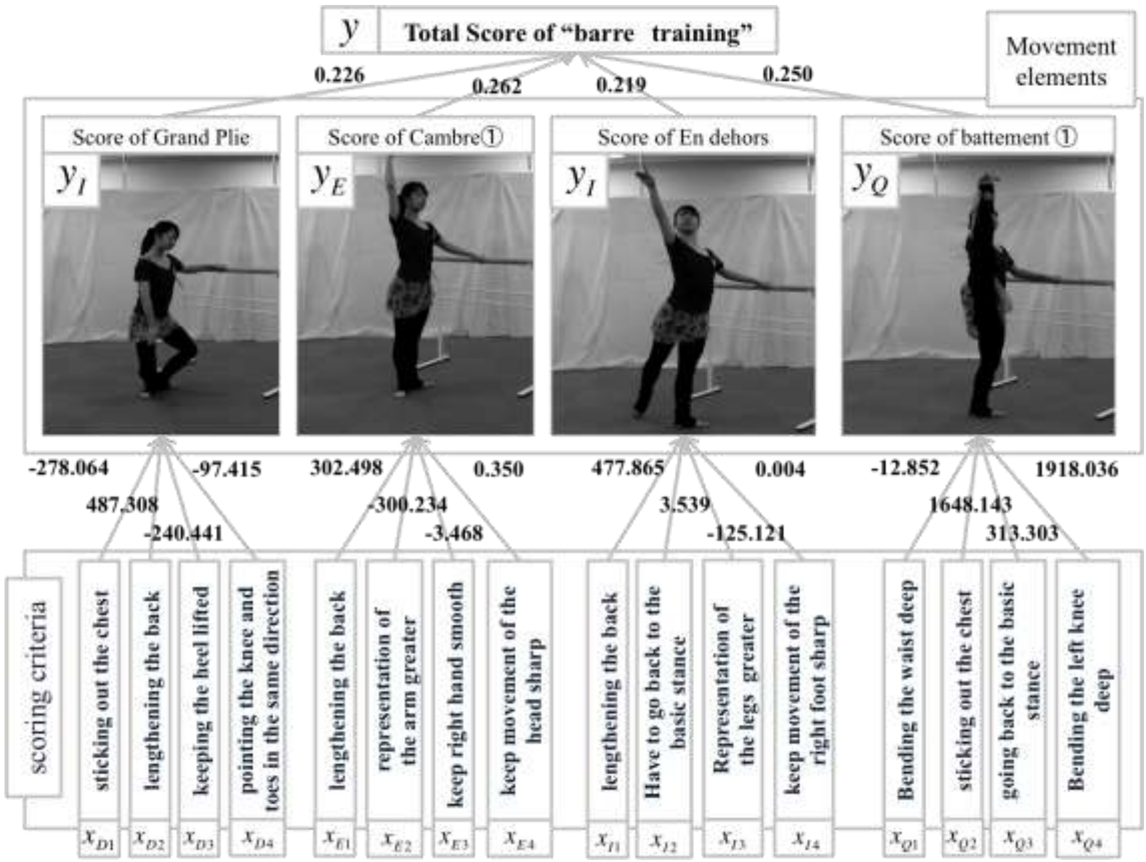

Figure 3: Relation between Total Score and Movement Factors

Table 5: Scoring Model Formula

$$y = 0.226y_D + 0.262y_E + 0.219y_I + 0.250y_Q + 2.689$$

$$y_D = -278.064x_{D1} + 487.308x_{D2} - 240.441x_{D3} - 97.415x_{D4} - 83.934$$

$$y_E = 302.498x_{E1} - 300.234x_{E2} - 3.468x_{E3} - 0.356x_{E4} - 610.672$$

$$y_I = 477.865x_{I1} + 3.539x_{I2} - 125.121x_{I3} + 0.004x_{I4} - 372.323$$

$$y_Q = -12.852x_{Q1} + 1648.143x_{Q2} + 313.303x_{Q3} + 1918.036x_{Q4} - 1517.57$$

The motion capture system was then used to collect new positioning data from ten ballet dancers performing barre training movements (plié and rond de jambe). Movement factor values were calculated and substituted in the formula in Table 5 to tabulate scores and come up with a ranking.

The six judges were then asked to score the barre training movements from the same ten dancers using traditional scoring methods (see Table 6). The totals were used to rank the dancers and the order of the results was compared with that obtained using the model. The rank correlation coefficient was 0.7333, indicating a high degree of consistency with the actual results (see Table 7 and Figure 4).

Table 6: Scoring Result by Traditional Scoring Methods

Dancers	Akoh	Kan-ichi	Kawai	Watanabe	Kaori	Chiho	Sum	Ranking
#1	65	78	63	73	60	75	414	6
#2	67	77	64	73	63	80	424	3
#3	64	76	64	75	63	75	417	5
#4	65	77	66	78	62	77	425	2
#5	60	70	65	74	59	79	407	7
#6	68	81	67	75	66	84	441	1
#7	66	79	67	76	61	70	419	4
#8	60	70	60	73	60	57	380	10
#9	65	72	58	78	65	62	400	8
#10	60	73	62	75	62	63	395	9

Table 7: The Rank Correlation Coefficient

Dancers	Score by Model	Ranking by Model	Total Score by Judges	Ranking by Judges	(Difference)^2
#1	65.30	5	414	6	1
#2	67.61	2	424	3	1
#3	65.24	6	417	5	1
#4	67.22	3	425	2	1
#5	62.05	7	407	7	0
#6	70.70	1	441	1	0
#7	66.33	4	419	4	0
#8	55.45	10	380	10	0
#9	61.22	8	400	8	0
#10	58.55	9	395	9	0
				Rank correlation coefficient	0.7333

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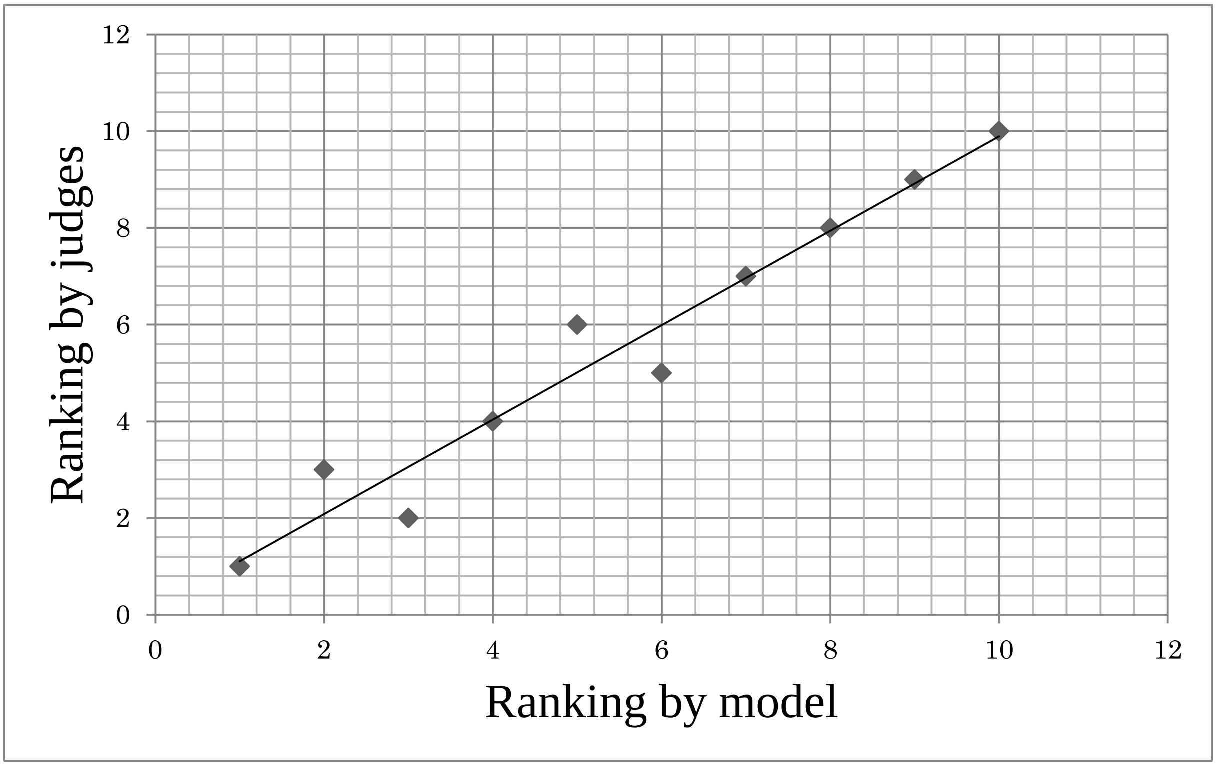

Figure 4: Relation between Ranking by Judges and Ranking by Model

Verification by Interview to Judges

Professional judges were interviewed on the scoring criteria obtained through this model. When the scoring criteria created in this study were suggested, the judges offered positive feedback, such as "taking a scientific approach to scoring could make it more fair", "I saw that there are some scoring items I'm not taking into consideration", and "this could help improve competitors' basic skills". Another judge remarked that scoring was easier once the scoring criteria had been clarified, indicating that the model meets a need among classical ballet judges.

CONCLUSION

The authors further used data collection, statistical analyses, and a verification/utilization workflow to create a scoring support approach model. Putting this approach model to use allowed the authors to offer scoring criteria for sporting events that may help address the problem of score variation among judges due to ambiguous scoring criteria.

Future studies are needed to build a scoring support approach model that considers artistic scores, a scoring evaluation system for other sporting events, and to further develop and utilize scoring support models.

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REFERENCES

1. Amasaka, K. (2002a), New JIT, A New Management Technology Principle at Toyota, *International Journal of Production Economics*, Vol.80, pp.135-144.
2. Amasaka, K. (2004), Development of "Science TQM", A New Principle of Quality Management : Effectiveness of Strategic Stratified Task Team at Toyota-, *International Journal of Production Research*, Vol. 42, No. 17, pp.3691-3706.
3. Amasaka, K. (2005), Constructing a Customer Science Application System "*CS-CIANS"*: Development of a global strategic vehicle "*Lexus"* utilizing New JIT –, *WSEAS Transactions on Business and Economics*, Vol.3, No. 2, pp. 135-142.
4. Amasaka, K. (2007), The validity of "TDS-DTM": A strategic methodology of merchandise development of New JIT - Key to the excellence design "LEXUS", *International Business & Economics Research Journal*, Vol. 6, No. 11, pp. 105-116.
5. Amasaka, K. (2008a), Science TQM, A New Quality Management Principle: The Quality Management Strategy of Toyota, *The Journal of Management and Engineering Integration*, Vol. 1, No. 1, pp. 7-22.
6. Amasaka, K. and Nagaya, A. and Shibata, W. (1999), Studies on Design SQC with the application of Science SQC -Improving of business process method for automotive profile design, *Japanese Journal of Sensory Evaluations*, Vol. 3, No. 1, pp. 21-29.
7. Amasaka, K. Customer science: studying customer values, *Japan Journal of Behavior Metrics Society*, Vol.32, No.1, pp.196-199.
8. Iino, Y. and Moriya, T. and Takahashi, T. (2011), Motion Analysis of Street Dance Performance and its Applications for Instructional Coaching, *The Institute of Image Information and Television Engineers*, Vol.35, No14, pp. 49-52.
9. Kudo, S. and Komura, T. and Ikeuchi, K. (2010), Modeling Balance Maintenance with Whole-body Motion Based on Observation of Human Motion, *MIRU2005*, Vol.2005, pp. IS3-111.
10. Kwon, I. and Nobuta, Y. and Park, N. (2010), Dance Sports in Korea: The Present Condition of Class and Participation in Korean Universities, Kyushu Kyoritsu University.
11. Ota, H. (2011), History of Dance Culture for Qualification Training by Actual Competition, *No Dance, No life*, pp. 20-30.
12. Takebuchi, S. and Amasaka, K. (2012), The Automobile Exterior Color Design Approach Model, Aoyama Gakuin University. (Unpublished) (in Japanese)
13. Yanagisawa, K. and Sato, D. and Hara, K. (2011), Constructing a Scoring Support Approach Model Using Motion Capture and Statistics, Aoyama Gakuin University. (Unpublished) (in Japanese)
14. Yazaki, K. and Tanitsu, H. and Hayashi, H. and Amasaka, K. (2012), A Model For Design Auto Instrumentation To Appeal To Young Male Customers, *Journal Of Business Case Studies*, Vol.8, No.4, pp. 417-426.

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